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Long exponentially distributed interbeat intervals in the ECG of patients with atrial fibrillation show white noise behaviour in power spectrum

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Abstract: The statistical properties of ventricular (RR) interbeat intervals during atrial fibrillation exhibit several characteristic features, such as a linear relation between the local mean and standard deviation obtained in small time windows (constant signal to noise ratio), a crossover in the power spectrum from a 1/f type at low frequencies to a white noise behaviour at high frequencies, and an exponential tail in the distribution of long RR intervals. We show in this work that these characteristic features are interrelated. The linear relation between the local mean and standard deviation can be used to classify the RR interval into two groups, where one gives the dominant contribution to the 1/f part of the power spectrum and the other the dominant contribution to the white noise part. Remarkably, the long RR intervals only contribute to the latter. Our results are useful to improve the characterisation of AF based on non-invasive surface ECG recordings.

Keywords – atrial fibrillation, time series analysis, tachogram, RR interval distribution, power spectrum, Lomb-periodogram

Characterisation of atrial fibrillation

Atrial fibrillation (AF) is the most common arrhythmia of the heart. It increases the risk of strokes [1] and of mortality [2] and leads to an impairment of physical ability (for a review, see e.g. [3]). A good classification and characterisation of AF is required to support the medical diagnosis and the choice of therapies. Several classification methods are based on the averaging of P waves [4, 5] and on the morphology of the intra-atrial ECG [6, 7, 8]. They often require invasive intra-atrial measurements with catheter electrodes. One promising non-invasive method for gaining information on atrial activity is to study baseline fluctuations in the surface ECG after subtracting QRS(or QRST) complexes [9].

Only a few studies have so far carried out where ventricular beat intervals are used for a better classification of AF. This is due to the fact that the ventricular beats only contain indirect information about atrial signals. Hayano *et al.* [10] analysed power spectra $S(f)$ of long term 24h recordings of RR intervals τ (tachograms). They found striking differences in the behaviour for healthy persons and patients with atrial fibrillation. Figure 1 shows the power spectra for two representative subjects (left panel: AF patient, right panel: healthy person) in a double-logarithmic plot. The data of the AF patients were taken from the pool analysed in [10] and the data for the healthy persons from the Physionet database [11]. For the healthy person in Fig. 1, $S(f)$ displays the typical "$1/f$ type behaviour" (corresponding to a power law $S(f) \sim f^{-\alpha}$ with an exponent close to one) over almost the whole frequency range. For the AF patient by contrast, a relatively sharp crossover is found, from a $1/f$ behaviour at low frequencies to a constant white noise behaviour at high frequencies. The crossover and the two different behaviours can be clearly seen in the left panel of Fig. 1.

In another study, Cammarota *et al.* [12] showed that the mean and standard deviation of the distribution $p(\tau)$ are linearly related in the case of AF. This holds true not only for the "global" mean $\overline{\tau}$ and standard deviation σ as calculated from all RR intervals, but also for "local values" that are obtained by an average over RR intervals in limited time windows. Figure 2 shows the local

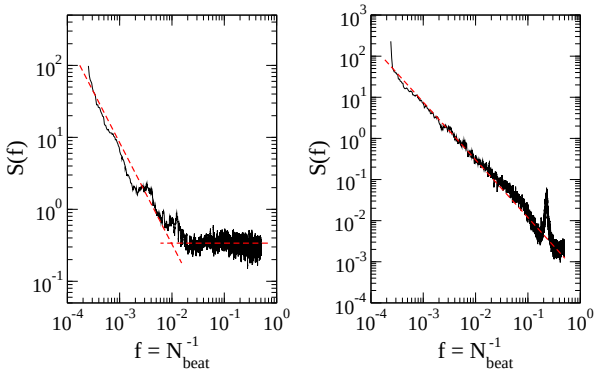

Figure 1: Double logarithmic plot of the power spectra of RR interval sequences for a representative AF patient (left panel) and for a representative healthy person (right panel). The data were calculated from tachograms of 24h ECG recordings and the spectra were smoothed with a moving average filter. The power spectrum of the healthy person shows a $1/f$ type behaviour up to high frequencies $f \gtrsim (10\,\text{beats})^{-1}$, corresponding to groups of less than 10 consecutive RR intervals. The power spectrum of the AF patient exhibits a crossover to a white noise behaviour at a frequency $f \simeq (100\,\text{beats})^{-1}$.

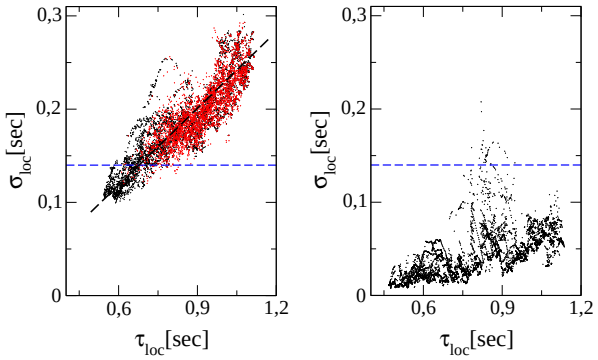

Figure 2: Local standard deviation $\sigma_{\rm loc}$ vs. local mean $\tau_{\rm loc}$ for the same subjects as in Fig. 1 (left panel: AF patient, right panel: healthy person). The local values were calculated for segments of 100 consecutive RR intervals. Points are marked in red when the RR interval τ in the centre of a segment satisfies $\tau > \tau_{\rm loc} + \sigma_{\rm loc}$, i.e. when it belongs to the exponential tail, and the dashed line marks the threshold $\sigma_{\rm loc}^{(c)}$ (see text).

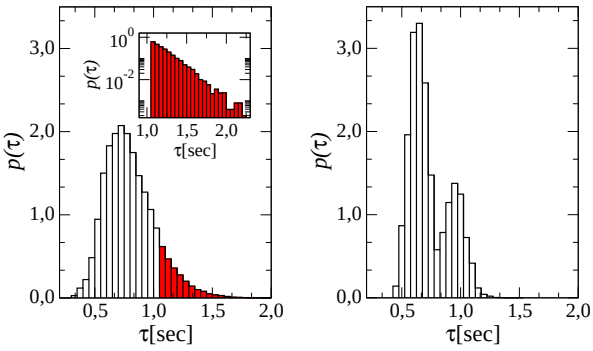

Figure 3: Distribution $p(\tau)$ for the same subjects as in Fig. 1 (left panel: AF patient, right panel: healthy person). The red bars mark the exponential tail in the distribution of RR intervals in the presence of atrial fibrillation. The inset of the left panel displays the exponential tail in a semi-logarithmic plot.

standard deviation $\sigma_{\rm loc}$ as a function of the local mean $\tau_{\rm loc}$ (black points) for the same subject as in Fig. 1 (left panel: AF patient, right panel: healthy person). Both $\sigma_{\rm loc}$ and $\tau_{\rm loc}$ were calculated for segments comprising 100 intervals $\tau_{\rm loc}$. While for the AF patient a linear behaviour $\sigma_{\rm loc} \propto \tau_{\rm loc}$ is seen, corresponding to a constant signal to noise ratio, no such behaviour is found for the healthy person.

A further characteristic feature of AF recently found by us is seen in the distribution $p(\tau)$ of RR intervals. For long intervals τ, the decay of $p(\tau)$ can be well described by a single exponential with decay rate γ,

$$p(\tau) \sim p_\infty e^{-\gamma\tau}\,. \qquad (1)$$

This behaviour is demonstrated in the left panel of Fig. 3, where the tail is marked with red bars (see also the inset in this figure). The tail region where eq. (1) is valid, generally encompasses all τ values satisfying $\tau > \overline{\tau} + \sigma$. By contrast, no exponential decay is found for the healthy person (see right panel of Fig. 3).

It can be shown that the distribution $p(\tau)$ during atrial fibrillation is reproduced when the RR intervals are decomposed into two parts, $\tau = \theta + \eta$, where θ has a distribution peaked close to the maximum of $p(\tau)$ and η has an exponential distribution. Physiologically, θ could be assigned to the sum of the conduction time and the subsequent refractory period of the atrio-ventricular (AV) node, when an atrial impulse has passed to the ventricle (i.e. the period, where further atrial impulses are blocked after the onset of an AV conduction process). The refractory period can be further decomposed into an absolute and a relative one, where in the former all impulses are blocked, while in the latter sufficiently strong action potentials are transduced (the threshold value decreases with time). Due to this effect the total refractory period fluctuates. Moreover, the conduction time (and also the absolute and relative refractory periods) depend sensitively on cell states (ion concentrations, permeability of ion channels) influenced by the autonomous nervous system. The time η is the time between the end of the (total) refractory period and the onset of the next conduction process. In contrast to θ, which is largely determined by properties of the AV node, η depends strongly on the statistical properties of the atrial interbeat intervals.

The characteristic features in the statistics of RR intervals discussed above are generic. The distinct properties described above are found also when comparing all 130 AF patients analysed in[10] with 72 healthy persons taken from the Physionet database [11].

Interrelation of characteristic features in the statistics of ventricular interbeat intervals during AF

The fact that AF is reflected in different and independent statistical properties of ventricular beat intervals, gives rise to the question if there exist interrelations between these properties. In particular we ask if the long RR intervals are associated with the white noise part in the power spectrum. With respect to the decomposition of the RR intervals into two times described above, the times θ should exhibit correlations that reflect a regulation by the autonomous nervous system, while the times η are uncorrelated (or exhibit correlations on very short times scales only). Due to the irregular fibrillatory activity it is moreover plausible that θ and η are statistically independent. As a consequence, the white noise part in the power spectrum is expected to result from the times η.

To test this idea we want to decompose the original sequence $\mathscr{S}$ of RR intervals into two sub-sequences $\mathscr{S}_1$ and $\mathscr{S}_2$, where $\mathscr{S}_1$ contains the intervals for which η gives only a small contribution ($\eta \ll \theta$), while $\mathscr{S}_2$ contains the intervals for which η cannot be neglected. The problem that a straightforward calculation of the power spectrum of $\mathscr{S}_1$ and $\mathscr{S}_2$ is not possible due to missing intervals in the sub-sequences can be resolved by approximating

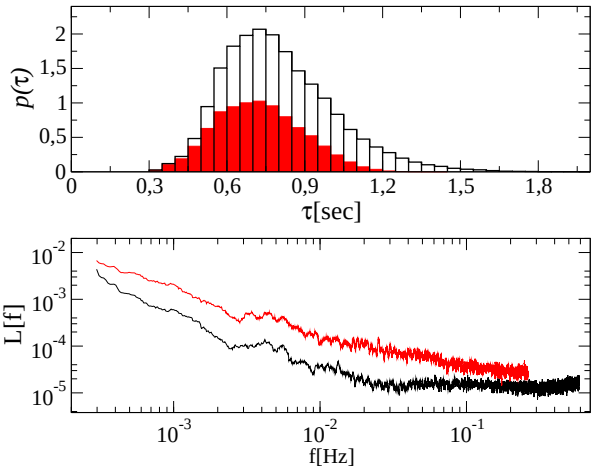

Figure 4: Distributions of RR intervals (upper panel) and Lomb periodograms $L(f)$ (lower panel) for the full sequence of RR intervals (black) and the sub-sequence $\mathscr{S}_1$ (blue). The data refer to the representative AF patient from Fig. 1 and the Lomb-periodograms were smoothed with a moving average filter.

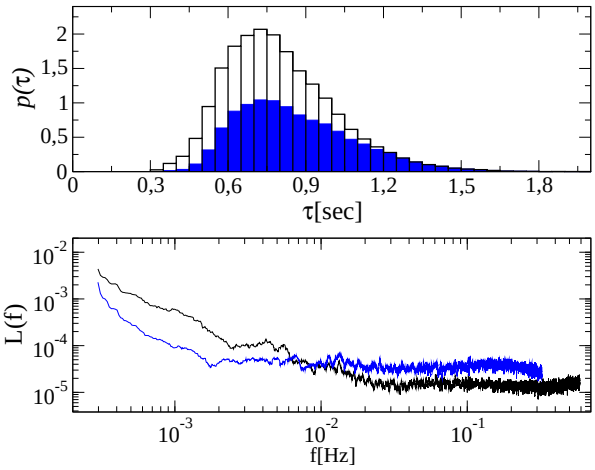

Figure 5: Distributions of RR intervals (upper panel) and Lomb periodograms $L(f)$ (lower panel) for the full sequence of RR intervals (black) and the sub-sequence $\mathscr{S}_2$ (blue). The data refer to the representative AF patient from Fig. 1 and the Lomb-periodograms were smoothed with a moving average filter.

the power spectra with Lomb periodograms [13, 14]. The white noise part in the Lomb periodogram of $\mathscr{S}_1$ then should be less significant, while it should be more pronounced in the Lomb periodogram of $\mathscr{S}_2$.

First we identified $\mathscr{S}_2$ with the sequence of long RR intervals that belong to the exponential tail in Fig. 3. However, such approach was only partly successful, since there exist also short RR intervals that contribute to the white noise part in the power spectrum.

A more successful procedure is to base the analysis on the constant signal-to-noise ratio $\sigma_{\mathrm{loc}}/\tau_{\mathrm{loc}}$ discussed above. In particular we found that segments centred around large RR intervals τ lie in the region of large σ_{loc} exceeding a threshold $\sigma_{\mathrm{loc}}^{(\mathrm{c})}$. This is demonstrated by the red points in Fig. 2, where the dashed line marks the threshold $\sigma_{\mathrm{loc}}^{(\mathrm{c})}$. These findings point to a clustering of large RR intervals, and they suggest to define the sub-sequence $\mathscr{S}_2$ by those RR intervals τ, which satisfy $\sigma_{\mathrm{loc}} > \sigma_{\mathrm{loc}}^{(\mathrm{c})}$ (the RR interval τ refers to the centre of the corresponding segment). Good results were achieved for segments of 10 consecutive RR intervals.

The resulting Lomb periodograms for the two sub-sequences $\mathscr{S}_1$ and $\mathscr{S}_2$ are shown in Figs. 4 and 5, respectively, together with the corresponding distribution function of RR intervals. For comparison the data for the full sequence of RR intervals are also shown in both figures. As can be seen from Fig. 4, the Lomb periodogram of $\mathscr{S}_1$ shows the $1/f$ type behaviour over almost the whole frequency range. The crossover to the white noise region in the periodogram of the original tachogram is shifted to the high frequency region. The RR intervals belonging to $\mathscr{S}_1$ have a distribution that barely contributes to the exponential tail seen in the distribution of all RR intervals.

A contrasting behaviour is seen in Fig. 5. The white noise regime in the Lomb periodogram of $\mathscr{S}_2$ extends to much lower frequencies compared to the Lomb periodogram of the full sequence of RR intervals, and the distribution of RR intervals belonging to $\mathscr{S}_2$ accounts for the whole exponential tail. In addition $\mathscr{S}_2$ contains also smaller RR intervals τ.

To summarise, the RR intervals belonging to the characteristic exponential tail seen in the distribution of AF patients contribute to the characteristic white noise regimes seen in the power spectra of AF patients. This supports the idea that the RR intervals during atrial fibrillation result from the superposition of two independent processes as described above.

Conclusions

We have shown that long RR intervals during atrial fibrillation are exponentially distributed and associated with the white noise part in the power spectrum. We developed a novel method to divide the tachogram in sub-sequences that dominate different parts of the power spectrum as well as different parts of the distribution of RR intervals. Our result indicate that RR intervals during AF result from a superposition of two statistically independent contributions. It is suggested that one of these contributions represents correlated effective blocking times of the AV node (sum of conduction time and refractory period), and the other uncorrelated times (recovery time) originating from the irregular atrial activity. We hope that further investigations of this approach will allow one to accomplish a better characterisation of AF, and consequently a more specific diagnose and improved choice of therapy.

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